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Research Article

Deep neural network multilayer perceptron for Parkinson's disease diagnosis using vocal data

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ABSTRACT

Parkinson's disease is a progressive neurodegenerative disorder that requires early diagnosis for effective management and improved patient outcomes. The traditional assessment methods are insensitive for early detection of the disease, which creates the space for development of accurate diagnostic techniques. This work presents the development and optimization of a deep neural network multilayer perceptron model for classifying Parkinson's disease using vocal features obtained from the University of California, Irvine, Machine Learning Repository. The dataset contains 22 speech-related attributes that capture motor deficits commonly observed in individuals with Parkinson's disease. The proposed framework consists of an input layer with 22 neurons, three hidden layers, and out of these three two hidden layers are each with 150 neurons and a third hidden layer with 50 neurons, and in the last a single-unit output layer, utilizing ReLU and sigmoid activation functions. To ensure reliability and strong generalization capability, the model was evaluated using a grid search strategy combined with 5-fold cross-validation. This validation scheme supports the development of a practical, non-invasive diagnostic aid for clinical use. The model demonstrated excellent performance, achieving an accuracy of 0.949, precision of 0.973, recall of 0.973, an F1-score of 0.973, and a specificity of 0.50. The results shown that the proposed model is most efficient over conventional classifiers such as support vector machine, random forest, and k-nearest neighbors. This study highlights the effectiveness of a deep neural network–based multilayer perceptron in enabling early and reliable identification of Parkinson's disease, indicating its value as a supportive instrument for clinical diagnosis.

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INTRODUCTION

Parkinson's disease (PD) is a persistent, contemporary neurodegenerative illness that considerably affects patient's standard of living. PD is described mainly by the worsening of dopamine yielding neurons in the substantia nigra region of the brain and shows with both motor and non-motor symptoms. Motor manifestations, involving tremors, bradykinesia, spasticity, balance disorder, are the key indicators of the illness. Non-motor signs, including dementia, affective disorder, insomnia, and dysautonomia are common and may even appear before motor symptoms [3]. The worldwide impact of impact of PD is significant, and it becomes significantly more common in older individuals. With the growing elderly population around the world, the prevalence of PD is predicted to raise, bolstering it as a major health crisis [4]. Timely identification of PD is critical for executing efficient methods that can sluggish the advancement of symptoms, enhance well-being, and reduce the health care expenses [23]. Due to lack of credible diagnostic tools, initial identification of PD remains difficult, as its symptoms are subtle and variable in nature. Conventionally, PD is identified through patient clinical review based on the existence of various motor symptoms. Neurologists commonly use the well-known frameworks, such as United Kingdom Parkinson's Disease Society Brain Bank (UKPDSBB) standard to identify the problem. But these Medical approaches have limitations. These methods are often inefficient to identify PD at early stages when signs are mild and non-specific. Though the conventional practice of parkinsosn's diagnosis is based on clinical assessment, which dependent on subjective decision. The conventional diagnosis results inconsistencies in diagnostic outcomes. Advances in neuroimaging and biomarker research studies have permitted earlier detection of PD. The degeneration of dopaminergic neurons in the brain can be more clearly identified through neuroimaging approaches such as DaTscan and PET, contributing to greater diagnostic precision. In addition, biomarkers including alpha-synuclein, DJ-1, and beta-amyloid are being studied for their relvance in identifying the disease. Nevertheless, these methods are usually expensive, and hard to implement, which limits their regular use in daily clinical activities. Under these restrictions, machine learning (ML) and deep learning (DL) techniques have appeared as potential approaches for automated detection of PD. These methods can analyze vast amounts of data and give precise predictions, often consistently outperforming conventional approaches. In the domain of PD, ML and DL have been used across diverse data types including patient health data, genomic data, and voice samples [30]. Among the above, speech examination has earned deep consideration because it is less intrusive and can detect early signs of vocal disorders in PD patients. Among the various approaches, speech-based analysis has attracted growing interest because it is non-invasive and because changes in voice often appear in the initial stages of Parkinson's disease. Difficulties related to voice production are frequent in affected individuals and may become noticeable even when the disorder is still in its early phase. These disorders mainly arise from motor impairments disturbing the larynx and associated muscles. Several vocal characteristics provides important intuitions and acts as clinical markers for PD [29]. Therefore, examining these vocal characteristics by means of ML and DL methods can help in the identification of the PD [1-2,5-6,8-11].

Support Vector Machine (SVM) is among the most used ML techniques for categorization. It works by finding best decision boundary that divides the given data into various categories. They are effective in multi-dimensional spaces and exhibit their strength to represent complex relationships with the help of kernel functions. In PD research, SVMs have been used to categorize people using several vocal characteristics, though their performance depends on the choice of kernel and hyperparameters, which is a problem for optimization [13]. k-Nearest Neighbours nearby (k-NN) is one more standard ML method used for categorization tasks. This direct, instance-based technique in which a sample is allocated to a category based on the principal class of its k adjacent elements. Its ease of use made it one of the prominent choices for various domains, including medical investigations [13]. In PD examination, k-NN has eased the categorization of patients using vocal parameters. Despite its simplicity, its performance depends on the choice of k and degrades as features increase. Random Forest (RF) is ensemble learning method that constructs many decision trees over training period and finalises their predictions by majority voting. It is popular for providing high precision, ability to process massive datasets, and improved generalization performance [7]. In PD research, RF has been applied to categorize patients using clinical and biological measures, with its attribute's relevance helping detection of key indicators. yet, RF models turn out to be computationally intensive, mainly when substantial numbers of trees are used. Regardless of the advantages of these classifiers, Deep Neural Networks (DNNs), especially Multilayer Perceptrons (MLPs), have shown exceptional capability in clinical evaluation with their ability to represent complicated relationships throughout the data. DNN-MLPs contain multiple neuron layers, comprising an input layer, one or more hidden layers, and an output layer. In this framework, each neuron in each layer is interconnected to neurons in the succeeding layer, with appropriate weights that are incrementally improved during the training [12]. In this work, a DNN-MLP architecture is proposed for the classification of PD using voice-based features. The proposed model is trained and assessed using the dataset from the UCI Machine Learning Repository [4], which encompasses 22 acoustic characteristics obtained from voice recordings. These characteristics are utilized to distinguish people with PD from normal people. Data preprocessing was carried out by using StandardScaler to balance all feature contributions and to retain only relevant features. Hyperparameter tuning is essential to improve performance of the DNN-MLP models. In the proposed work, GridSearchCV is used to examine different DNN-MLP architectures. The proposed model performance is evaluated by various metrics such as accuracy, precision, recall, F1-score, and specificity. Further, for benchmarking, conventional ML models such as SVM, RF, and k-NN are also deployed and verified using the same dataset.

MATERIALS AND METHODS

The dataset utilized in this work is obtained from the Parkinsons Telemonitoring dataset available at UCI machine learning repository. The dataset consists of speech samples and related clinical information collected from both Parkinson's disease patients and healthy individuals. The dataset is obtained from sustained voice quality recordings, from which a set of sound descriptors were obtained to describe speech variations linked to motor impairment. Besides these vocal features, the database also contains demographic details, such as age and gender, as well as assessment metrics, such as motor scores from the Unified Parkinson's Disease Rating Scale (UPDRS). For categorization, an indicator variable named as status is declared; if its value is '1', it indicates the presence of PD and '0' corresponds to a healthy person, based on medical diagnosis and motor appraisement. Acoustic features are fundamental frequency, jitter, shimmer, and harmonics-to-noise ratio (HNR), which are sensitive indicators of vocal pathology associated with PD. The obtained data is preprocessed before taining the model. The preprocessing involves like data splitting, feature scaling, missing data handling and feature selection. In the process of data splitting the dataset is divided into training and testing subsets using an 80:20 split ratio. The data splitting method employs stratified sampling to preserve equal quantities of individuals with and without PD across all divisons, which help minimize selection bias. In the process of feature scaling, continuous features are standardized using the Standard Scaler. This process transforms the feature space to have a mean of zero and a standard deviation of one, ensuring that all features contribute equally to model training without undue influence from variables with larger scales. During data preprocessing, any absent values are addressed using suitable methods, such as replacing them with the median, chosen according to the data distribution and the pattern of missing entries. The features are selected based on their clinical relevance and statistical importance to reduce the dimensionality and enhance the clarity of the model. As a result, we train and validate the ML models with the transformed data.

Recent research has shown that using ML techniques can aid in the diagnosis of PD through speech signals. A Multilayer Perceptron (MLP) classifier attained the highest recognition rate of 91 %, outperforming Support Vector Machine (SVM) and k-Nearest Neighbors (k-NN), both of which recorded an accuracy of 87.17 % (Rana et al. (2022)), This shows the potential of these neural network-based models for this application [32]. In a related study, tai et al. in 2021, evaluated a dataset of 1,400 voice recordings and 70 acoustic features and supported that SVM is a best classifier with an accuracy of 88 % [31]. These studies support the use of voice characteristics as reliable digital biomarkers for Parkinson's disease and indicate that further investigation of such methods could improve diagnostic accuracy and accessibility.

In the present work, four machine learning models are developed and assessed such are, a widely used supervised learning model i.e., SVM, a non-parametric classifier i.e. k-NN, an ensemble based technique i.e. RF and the proposed model, Deep Neural Network-Multilayer Perceptron (DNN-MLP), which comprises mutiple fully connected layers capable of learning highly intricate data representations. To decrease overfitting and increase its capability for early PD detection, the proposed mrthod uses adjustable hidden-layer settings, ReLU activations, and suitable regularization techniques.

Training and testing are performed after model construction for each classifier. The learning phase emphases on fitting each model to the training data subset, allowing it to learn input-to-output associations effectiviely. A hybrid approach of grid search optimization and five-fold cross- validation is then applied to fine-tune hyperparameters- such as regularization terms, learning rates, and batch sizes in the DNN-MLP, and kernel parameters in the SVM-with the goal of improving generalization performance. Performance is measured using widely accepted evaluation criteria, including accuracy, precision, recall, F1-score, and specificity, the latter reflecting the model's capability to correctly identify health individuals [24]. All the developed models are ranked using comparative assessment based on their evaluation outcomes in the classification.

ARCHITECTURE OF DNN-MLP

The architecture of DNN-MLP consists of three main layers. The first layer of the network is the input layer, which is used to receive the input data. İn this neural network, the each feature of the dataset is represented by neuron, in this work, the dataset consists of various biomedical measurements, and the number of neurons are corresponding to the number of features. The last layer is the output layer and which produces the network's final predictionsBetween the input and output stages lie one or more hidden layers made up of neurons that compute weighted combinations of the incoming signals and pass them through activation functions. The number of layers and the number of neurons within each layer are critical determinants of the network's performance and are selected based on the complexity of the underlying problem. In applications such as Parkinson's disease detection, a DNN-MLP may therefore include multiple hidden layers so that subtle and non-linear patterns in the data can be learned effectively. The complete structure of proposed method is shown in Figure 1.

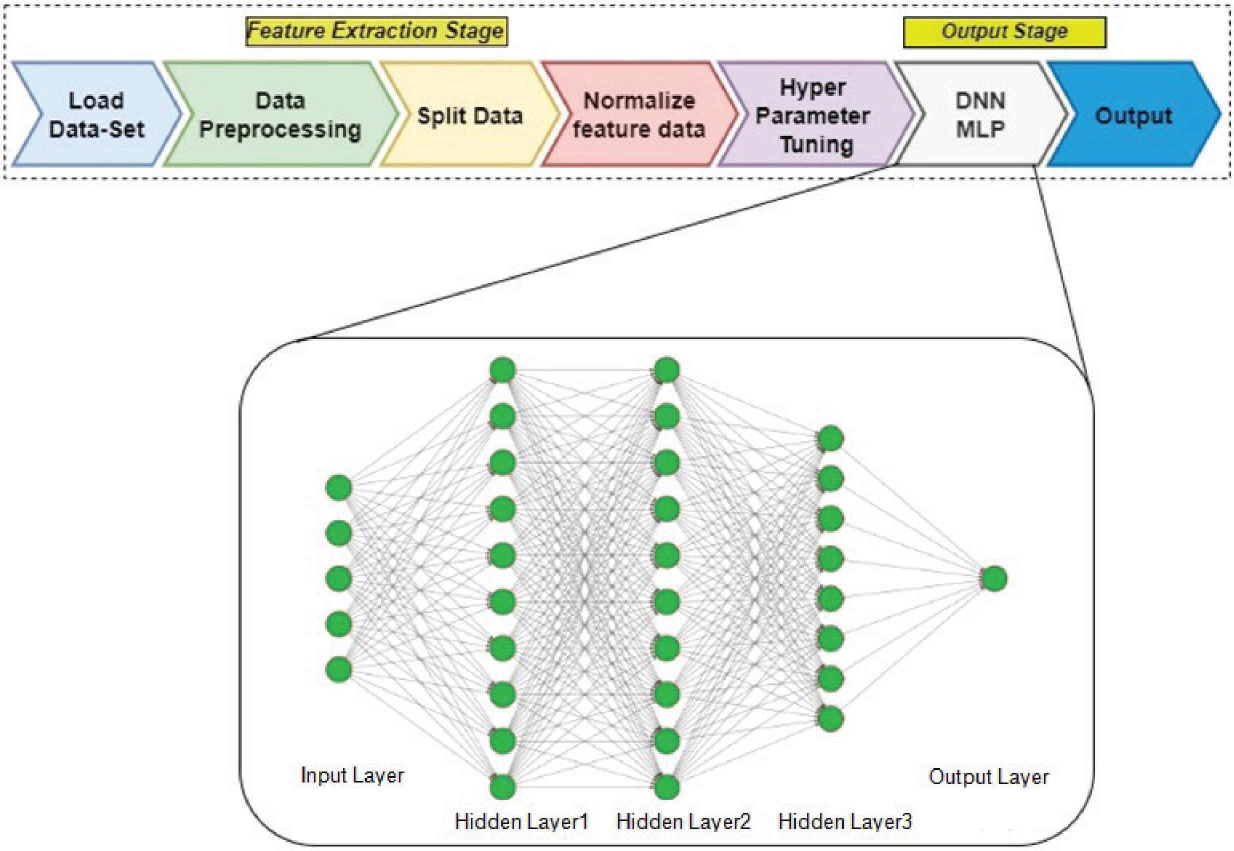

Figure 1. Block diagram of proposed model.

a) Activation Functions

Activation functions are required to introduce nonlinearity into the network to learn complex patterns in the data. The mainly used activation functions in this proposed model are, ReLU (Rectified Linear Unit) and Sigmoid.

$$f(x) = max\ (0, x) \tag{1}$$

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

RELU is used in hidden layers to mitigate the vanishing gradient problem and accelerate convergence [12,15]. Sigmoid is used in the output layer for binary classification to map the output to values 0 and 1, allowing them to be intepreted as class probabilities [16,20].

b) Weight Initialization

The initialization of weights plays a significant role in the learning process of a deep neural network, as improper intilization leads to ineffective convergence. There are various approaches for intializing the weights, the simple approach is zero initialization, where all weights assigned with zero but this is not widely used because it forces all neurons to behave identically during training. One extensively utilized approach is random initalization, where each weight is assigned a arbitrary initial value, helping different neurons to capture diverse feature representations during training. A distinct approach, known as He initalization, initializes the weights using a scaling factor relative to the number of neurons present in the preceding layer. This method is particularly suitable for networks employing ReLU activation functions, as it maintains signal varaince across layers [22].

c) Forward Propagation

During forward propagation, input data propagates through successive network layers untill a final prediction is generated. At each layer, every neuron receives inputs from the preceding layer, calculates a weighted of the inputs, and then employes its activation function prior to forwarding the output to the subsequent layer. This procedure is repeated through all layers untill the final layer generates the network's final prediction [12]. The calculation executed by a single neuron can be described by,

$$z_i = \sum_{j=1}^{n} w_{ij} x_j + b_i \tag{3}$$

$$a_i = f(z_i) \tag{4}$$

where z_i denotes the weighted sum, w_{ij} represents the connection weights, x_j refers to the input values, b_i is the bias, and $f(z_i)$ is the applied activation function.

d) Loss Function

To assess how well the model performs, a loss function calculates the difference between the predicted outputs and the actual output values, control parameter updates all through the training process [15]. In the designed framework, binary cross-entropy serves as the loss function, defined as

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i) \qquad (5)$$

Where, y_i denotes the true class label, $\hat{y}_i$ represents the predicted probability, and N is the total number of training samples.

e) Backpropagation and Optimization

Backpropagation is the core learning mechanism used for training neural networks. It consists of two main phases, a backward pass followed by weight updates. In the backward pass, the gradients of the loss function with respect to each network parameter are computed using the chain rule of calculus. This step calculates how much the loss function will change with respect to a small change in the weights. As well as weight update adjust the weights in the direction that reduces the loss using an optimization algorithm such as Stochastic Gradient Descent (SGD) or Adam [20].

f) Regularization

The overfitting is controlled by various regularization techniques including L2 regularization and dropout. By adding a squared weight penalty in the loss function, L2 regularization controls model parameters that can lead to overfitting. This also improves the model's capability to perform well on new data. In contrast, dropout randomly turns off a proportion of neurons during a training iteration to curb robust dependencies among neurons and encourages the model to learn bettter features. [21–22].

g) Hyperparameter Tuning

The choice of hyperparameters strongly influences the efficiency of DNN-MLP. The number of hidden layers and neurons, the learning rate, and batch sizes, as well as regularization settings. To find suitable values, we typically employ an optimization method (like grid search or random search) that tests different parameter combinations in order to select the one that provides the highest performance [16–17].

h) Model Evaluation

The execution of the model is examined using different performance indicaters including accuracy, precision, recall, F1 score, and specificity, once training is over. The performance relies on proper hyperparameter selection and regularization techniques. These enable the model to achieve desirable performance without overfitting. [14,33].

RESULTS AND DISCUSSION

The dataset used in this study is the Parkinson's Disease dataset from the UCI Machine Learning Repository. The dataset consists of 195 samples and 23 attributes. The main features of the dataset are fundamental frequency (MDVP: Fo(Hz), MDVP: Fhi(Hz), MDVP: Flo(Hz)), several measures of variation in fundamental frequency (MDVP: Jitter(%), MDVP: Jitter(Abs), MDVP: RAP, MDVP: PPQ, Jitter: DDP), several measures of variation in amplitude (MDVP: Shimmer, MDVP: Shimmer(dB), Shimmer: APQ3, Shimmer: APQ5, MDVP: APQ, Shimmer: DDA), two measures of ratio of noise to tonal components in the voice (NHR, HNR), and six nonlinear dynamical complexity measures (RPDE, DFA, spread1, spread2, D2, PPE). Within the dataset, output classes are binary, with '1' assigned to validated positive instances to have PD and '0' representing healthy controls. The model performance is evaluated using grid search optimization and five-fold cross- validation could yield better results than using either one separately. By employing this validation procedure, it helps mitigate overfitting and provides a reliable assessment of the model's capacity to generalize to unseen data. The dataset is split into training and testing subsets using 80: 20 split, where 80 % is used for training and other 20 % is a held-out test for unbiased performance assessment. The division of data into 80 % for training and 20 % for testing is a practical choice since other ratios may hinder generalization or introduce greater variability. For comparative analysis, four classification models are considered: SVM, k-NN, RF, and DNN-MLP. The DNN-MLP model is used the hyperparameter tuning using GridSearchCV to find the optimal configuration. The hyperparameters are tuned to include hidden layer

Table 1. Performance metrics for SVM, RF, k-NN and DNN-MLP

Model	Accuracy	Precision	Recall	F1 Score	Specificity
DNN-MLP	0.949	0.973	0.973	0.973	0.500
SVM	0.872	0.971	0.892	0.930	0.500
Random Forest	0.923	0.972	0.946	0.959	0.500
k-NN	0.923	0.972	0.946	0.959	0.500

sizes, activation functions, solvers, alpha values, learning rates, and early stopping criteria. The effectiveness of the proposed models is assessed using a set of standard performance measures. The accuracy is the proportion of correctly classified samples as compared to the entire samples. Precision indicates the proportion of instances identified as positive that truly belong to the positive class. Recall or sensitivity reflects the extent to which actual positive cases are identified by the model. Instead of treating precision and recall as separate indicators, the F1-score takes both into account and calculates their harmonic mean. Specificity assesses the capability of the model to correctly predict negative class which give rise to true negatives. Moreover, it's given as the ratio of true negatives out of all actual negative instances. Besides these individual metrics, confusion matrices are constructed which provide an overall view of the class predictions where both the correct and incorrect predictions are easy to understand. The test results of the various models are summarized in Table1. The proposed DNN-MLP provides a performance score of 95% accuracy, 100% recall, and a 97% F1-score in PD detection. These results are better than those reported by several approaches. For instance, Rana et al. (2022) reported that their MLP model achieved an accuracy of 91%, whereas both k-NN and SVM achieved 87.17% [32]. In a related study, Tai et al. (2021) observed that SVM produced an accuracy of 87.2%, confirming its effectiveness for this type of data [31]. Random Forest classifier is proved as the efficient classifier with an accuracy around 93%, whwreas in the medical diagnosis tasks, the data is non-linear and it consists of complex pattwerns. For such data patterns, the DNN-MLP is suggested as the best suitable technique.

For each classifier, performance measures such as accuracy, precision, recall, F1-score, and specificity were obtained from the confusion matrix generated using the test data. The confusion matrices of all the implemented models are as shown in Figure 2. The SVM classifier also demonstrated

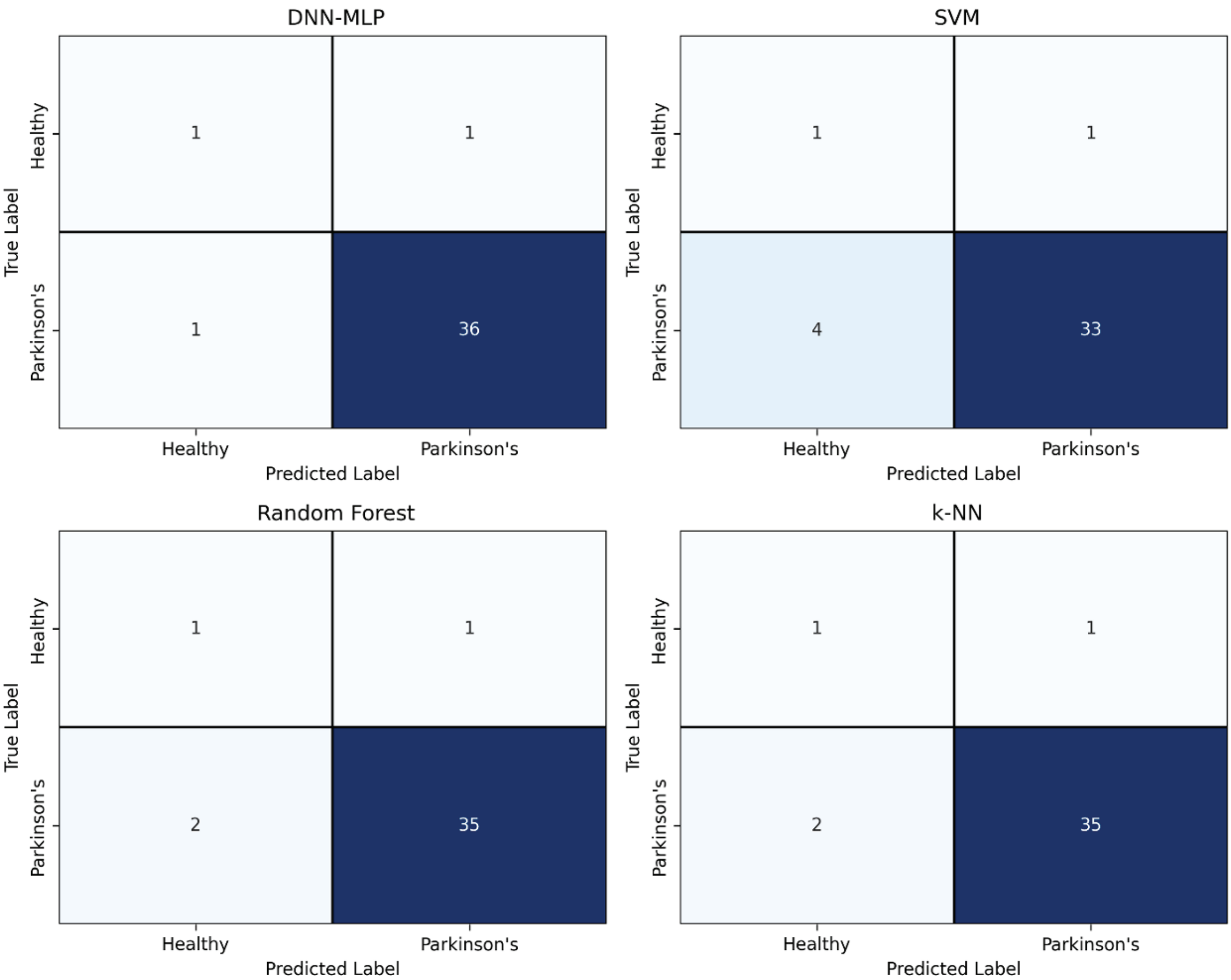

Figure 2. Confusion Matrices of DNN-MLP, SVM, RF, and k-NN.

strong performance, achieving high precision and recall, which reflects its effectiveness in distinguishing healthy individuals from patients with PD, although its overall results were marginally inferior to those of the DNN-MLP. The RF model attained a higher recall value; however its precision and specificity were relatively lower. This indicates that while it successfully indentified most true positive cases, it is also genrated a large number of false positives compared to the DNN-MLP and SVM classifiers.

Finally, the k-NN classifier showed performance equal to that of the RF model, but which can be attributed to its sensitivity to the selection of the k value and chosen distance metric. A comparison of the evaluation metrics for all models is shown in Figure 3 as a bar plot.

The Figure 3 shown above, depicts how the DNN-MLP odel is giving better results than SVM, Random Forest, and k-NN. Additionally, the distributions of Harmonics-to-Noise Ratio (HNR) and Noise-to-Harmonics Ratio (NHR), two critical voice features used in identifying Parkinson's disease in the dataset were analyzed and shown in Figure 4. HNR distribution indicates the ratio of harmonics to noise in the voice samples, which distinguishing between healthy and Parkinson's patients. NHR distribution shows the ratio of noise to harmonics,

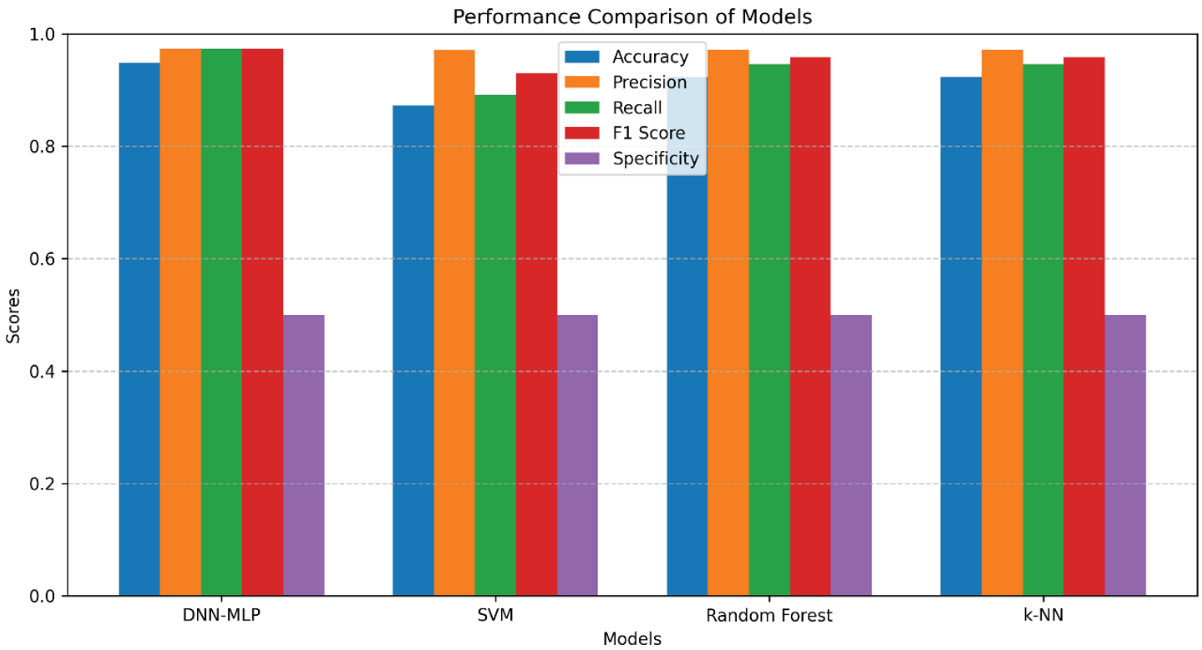

Figure 3. Metrics comparison of DNN-MLP, SVM, RF and k-NN.

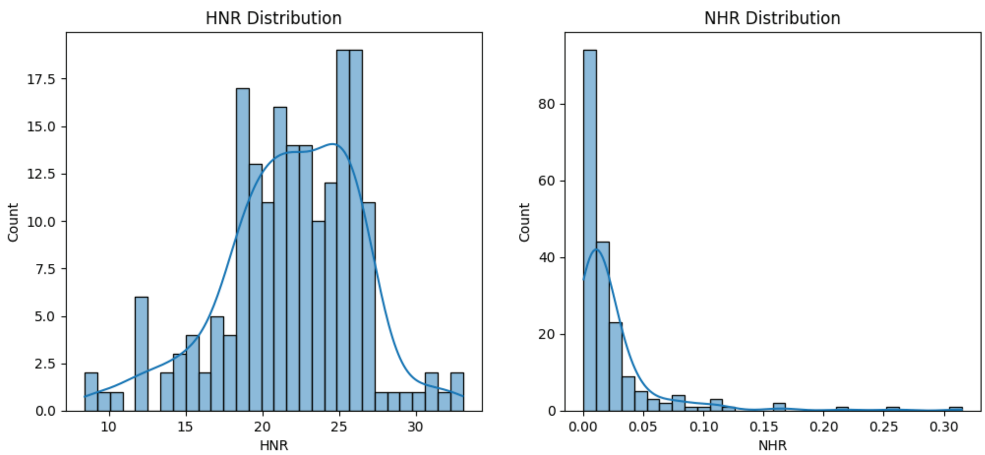

Figure 4. NHR and HNR distribution.

providing complementary information to HNR. The HNR distribution clearly demonstrates the healthy individuals with higher HNR values and with strong harmonic contents. The distribution consists of higher and lower HNR values. The higher values are representing the healthier vocal qualities and lower HNR values are representing the vocal qualities of Parkinson's disease.

The classification results proved that the DNN-MLP model is the best suitable model for the diagnosis of Parkinson's disease from voice measurements. The performance achieved by the proposed model is showing the ability of the deep architectures. The hyper parameter tuning is also be considered as very useful in the improvement of efficiency. The DNN-MLP outperforms the other models across all key performance metrics, suggesting that it is most effective approach for the dataset examined. Although the Random Forest and k-NN classifiers produced acceptable results, their performance remained below that of the DNN-MLP and SVM. This indicates that, while these methods have practical value, they may be less dependable for the early identification of Parkinson's disease when relying on speech-based features.

CONCLUSION

The proposed DNN-MLP model for Parkinson's disease diagnosis using biomedical voice data is evaluated against conventional machine learning methods, including support vector machine, k-nearest neighbors, and random forest. The dataset obtained from the UCI Machine Learning Repository comprised 195 samples described by 23 voice-related features. A detailed comparative analysis across all classifiers was performed using accuracy, precision, recall, F1-score, and specificity as evaluation benchmarks, with to determine each model's efficiency in distinguishing between PD-affected and healthy individuals. Across all experiment trials, the DNN-MLP appeared as the most consistent classifier, maintaining consistent performance in the vicinity of 0.949 for every metric considered. The depth inherent to its neural architecture plays a major role in this achievement, enabling the model to effectively detect and encode subtle, non-linear dependencies embedded in the vocal feature representations. The results shown that, the proposed architecture is proved as an outerperformed model than conventional machine learning approaches in the early diagnosis of parkinson's. Additionaly, such automated systems may help streamline diagnostic procedures and extend access to healthcare in resource-constrained settings where specialist expertise is limited. Future research may focus on integrating additional data modalities, including clinical evaluations, neuroimaging information, and genetic markers, to further improve the robustness and generalizability of the proposed approach.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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